The Impact of Displaying Quantity Scarcity and Relative Discounts on Sales and Consumer Returns in Flash Sale E-Commerce

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Abstract

Flash sale e-commerce is a very competitive business with low margins due to the high discounts granted. Against this background, merchants pursue the goal of generating as many orders as possible. To achieve this, techniques that stimulate impulse buying behavior are often used. This paper examines two specific instruments that have the potential to contribute to impulse buying, namely, the on-site display of (1) scarcity notifications and (2) the relative discount provided. We use real-world data from a flash sale e-tailer to analyze the impact on customer sales and returns. In that regard, this study is the first to focus specifically on fashion, which is the product category most affected by returns. Furthermore, to synthesize both perspectives, a quantitative model is presented to serve as the basis for a decision support system that enables managers to better deal with the underlying trade-off.

1. Introduction

Imagine the following self-talk of someone who spotted a great offer in a flash sale community:

"*I really like that brand… Let's have a quick look at what they are offering… Wow, 60 % off, that's quite a deal! Hmm, but only two left. I have to act fast.*"

A week later, after the parcel carrier delivered the order:

"*Well... that's not really what I expected. I think maybe I rushed it. But, no, I don't like it… It definitely needs to go back. Great that they offer free returns.*"

When reading these lines, many passionate online shoppers might experience a déjà-vu. This example illustrates the weal and woe of every e-tailer. First, customers have to be persuaded to order. For that purpose, e-tailers use on-site marketing tools to stimulate the customer's impulse buying behavior and thus increase order likelihood. These include, among others, displaying price discounts and disclosing the limited remaining stock. However, such measures may also affect the probability that consumers develop buyers' remorse. Since customers cannot physically assess the quality and fit of products online, returns are an inevitable part of the business model [1, 2]. Merchants of fashion products with return rates of 50 % and more are particularly affected [3]. Although relative return rates declined slightly during the COVID-19 pandemic, the absolute number of consumer returns continued to rise due to the massive growth in e-commerce [4].

With such high return figures, ordinary e-tailers already face problems of operating profitably. For flash sale e-tailers, however, the challenge is even more pressing. Specialized flash sale e-tailers such as HauteLook, Gilt, BestSecret, VIP.com – some of them among the leading fashion e-commerce companies worldwide [5] – build a closed shopping community for which they organize private sales with highly discounted products of popular brands for a limited period. The products are on offer until sold out or the campaign period ends.

Flash sale shopping club platforms are a popular distribution channel among well-known brands since the closed community prevents the cannibalization of their primary markets while having the opportunity to market the excess stock at the end of the selling season. In general, flash sales are a commission business. This means that the flash sale e-tailer receives a percentage of the sales price for organizing the sale and processing the orders and returns. Any unsold items are returned to the brand manufacturers. The margins of the business model are significantly lower than those in regular retail due to the high discounts. For this reason, it is essential for flash sale e-tailers to generate as many orders as possible. At the same time, however, the return rates must not be too high. Against this background, this paper addresses the following research question:

To what extent do the display of quantity scarcity messages and price discounts impact sales and consumer returns in a flash sale e-commerce environment, and how does it influence profitability?

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To answer this research question, we use real-world data from a leading specialized flash sale e-tailer, as Pavlou et al. [6] recommended. This study contributes to the digital commerce and electronic marketing literature by examining the impact of on-site communication efforts on both dimensions of the underlying problem: (1) sales and (2) returns. Furthermore, we present a quantitative model that integrates both perspectives and may serve as the basis for a decision support system that puts decision-makers in the position to better deal with the underlying trade-off.

The remainder of this paper is organized as follows: The following section presents backgrounds, the relevant literature, and the development of our hypotheses. The methodology and the data used are presented in Section 3. Section 4 contains the analysis of the data and a discussion of the results, while Section 5 illustrates a generalized approach for assessing the profitability of interventions. Finally, we conclude with an outlook and future research opportunities in Section 6.

2. Background, literature review, and derivation of hypotheses

2.1. Background

As described in the introduction, triggering impulse purchases is one of the most effective instruments to increase orders. Impulse buying "[…] describes any purchase which a shopper makes but has not planned in advance" [6]. Often, visuals at the point-of-sale (or on the respective website) trigger impulse purchases. Major influences for impulse buying are, for example, low prices, marginal need for an item, or prominent store display [6]. Thus, impulse buying can be stimulated by instruments such as communication or price stimuli [7]. Pricing-oriented instruments have long been used in marketing to attract customers and increase sales, such as time-limited discounts or VIP customer treatment [8].

Another measure to attract e-commerce customers could be the limited availability of products. Scarcity messages increase perceived arousal and thus positively impact impulse purchases [9]. This effect can be attributed to limited time or limited quantity [10, 11]. Flash sale e-tailers use both types. Time scarcity refers to an offer becoming unavailable after a certain period. Limited quantity scarcity refers to an offer only being available as long as supply lasts. As soon as the retailer displays the remaining stock on their webshop, the latter kind of scarcity creates uncertainty and the urge to order quickly because the behavior of unknown others determines one's own outcome.

Such "[…] use of user-interface design elements to guide people's behavior in digital choice environments […]" [12] is referred to as digital nudging. User-interface elements support and influence decision-making without imposing significant economic incentives or restricting the freedom of choice [13]. The recent discussion about digital nudging includes increasing personal or social welfare [14, 15] to better distinguish these interventions from marketing techniques such as dark patterns, undermining the consumers' best interest [14]. Against this backdrop, information on e-commerce websites such as messages about product scarcity or the display of relative price discounts acts as a digital nudge, at least in a broader sense.

In general, but even more so in the flash sale context, purchases in online retailing entail uncertainties, which can be categorized into product quality/fit and valuation uncertainty [15]. Impulse buying with little time to inform oneself about the product decreases the probability of a good fit or developing realistic expectations about the product [2]. In contrast, low prices can reduce valuation risk by lowering the expectations to be met. To minimize the perceived uncertainties, create trust, and encourage consumers to order, companies are granting liberal return policies, leading to more returns than in traditional brick-and-mortar retailing [e.g., 16]. Since the costs caused by returns do not rise linearly but disproportionately with the return rate, returns management is considered a critical success factor for overall profitability [17]. In flash sale e-commerce, returns are even more crucial because of the below-average margins.

2.2. Relevant literature

One strain of literature this work relates to is the **design and information value of retailers' shopping websites** (e.g., the use of product-related content such as zoom features [1] or customer product reviews [18]). Scarcity or discount messages act as instruments to catch customers' attention and influence their behavior. This has been studied by Luo et al. [19] for cart targeting. They found that scarcity and price incentives can promote sales if specific requirements are met. According to their field experiment, price incentives were relatively ineffective before an item was shortlisted to a user's cart. In contrast, costless scarcity messages significantly boosted purchases and were superior to price incentives.

The second stream of literature specifically investigates **scarcity and its effect on sales**. Following signaling theory, scarcity messages signal product quality for consumers with limited information [20]. Although the low stock boosts sales and consumer competition, sold-out products are a reason for consumer dissatisfaction [21]. Cui et al. identify flash sale customers from Amazon Lightning Deals and show that low stock situations increase their order likelihood [22]. Calvo et al. [23] replicate this finding for another flash-sale retailer, where the disclosure of scarcity increases hourly sales by 13.6 %. In contrast to most literature, Park et al. [24] observe decreased sales of durable goods when partial stock information ("less than five items left") is displayed.

Concerning the **display of price discounts to promote sales**, Lehtimäki et al. [25] and Choi and Coulter [26] discuss different variants of displaying price discounts (e.g., absolute and relative discounts under different price levels). While some papers examine how the price level influences return behavior, we do not know of any previous work investigating the effects of visual cues regarding the granted discount on consumer returns.

Concerning the reverse part of the e-commerce supply chain, few scholars have investigated the **effects of scarcity on returns**. Rao et al. [27] analyze online channel transaction data from a personal accessory retailer to show that quantity scarcity perceptions increase the likelihood of a return. Ishfaq et al. [28] model and simulate the probability of returns under scarcity and price leadership conditions with data from an e-tailer. They conclude that products with low stock are more likely to be returned, but low stock interacts with the effects of price leadership. In their analysis, price leadership significantly reduces returns. Contrasting empirical findings from most other works, actual sale prices do not affect returns. Apart from that, Cook and Yurchisin [29] survey young fashion retailer customers. According to the results of a structural equation model, perceived scarcity and low prices increase impulse buying, which relates to negative postpurchase emotions and thus an increased probability of returning. Finally, Calvo et al. [23] examine the effects of disclosing low stock on sales, returns, and resulting net sales with the data of a flash sales retailer that offers a wide product assortment. Disclosing product availability increases all of the variables mentioned, suggesting that additional sales effects generally outweigh losses from returned goods, while their base return rate equals just 5.4 %.

This points to our contribution: By combining the highlighting of price discounts and their effects on returns, we widen the agenda of Li et al. [8]. They aimed to study the impact of pricing-related web technologies on product returns. We also respond to the call for research by Toktay et al. [30] and Rogers et al. [31] to identify factors that influence returns. We complement by investigating the effect of discount disclosure not only on sales but also on consumer returns. This study also aims to resolve the reported inconsistencies regarding the impact of scarcity messages on sales (e.g., [23, 24]). Furthermore, to check the generalizability of these results, unlike Calvo et al. [23], who investigate data from an e-tailer with low return rates, we look into the most affected product category: apparel. In addition, we present a quantitative model to substantiate managerial decisions regarding the business case of such measures.

2.3. Hypothesis development

As consumers do not know a product's initial stock, information about low remaining stock triggers the perception of high demand. This leads to two distinct reactions. First, consumers obtain the impression of high product quality (e.g., due to a low level of information) [20]. Moreover, consumers conclude that an offer's price is highly attractive. This herding effect, when consumers draw inferences from the behavior of others and try to imitate their behavior regardless of their own information [32], was empirically documented by Cui et al. [22] for retail customers. Second, perceived scarcity urges consumers to decide whether to order in a limited amount of time. This can be attributed to the scarcity effect, which describes the occurrence of buying frenzy by incompletely informed customers in anticipation of out-of-stock situations: Any customer who waits too long will find no more units available [33]. Lower product availability is then accompanied by the perception of a higher product value making the product more attractive [10].

Scarcity also increases the customer's attention to scarce products [34] compared to highly available products, which applies especially in flash sales with mostly restricted stock, leading to more impulse purchases due to higher arousal. Furthermore, fashion is a product category strongly associated with impulse purchases [35]. Therefore, we hypothesize:

H1. Displaying product scarcity increases sales in a flash sale e-commerce environment.

It is well accepted that price savings create an incentive for purchasing [36–38]. Price and discount communication frame price evaluations as well as the subsequent purchase decision [39]. Customers implicitly estimate the difference between price quotes in relative terms (approximately 50 percent off) [40]. That is why a price reduction from \$50 to \$30 is perceived as more beneficial than a price reduction from \$100 to \$80, although the absolute discount is identical [26]. When the value of goods is low, indicating a relative discount promotes the perception of the offer as favorable [25]. This applies to the present case, as clothing is generally in a low- to medium-price segment. Besides, the display of a relative discount in addition to recommended retail prices and reduced prices lowers the cognitive effort required to estimate and classify the discount following mental accounting theory [26]. Therefore, impulsive buying is promoted since the information evaluation phase before the purchase decision is shortened. Consequently, we hypothesize:

H2. Displaying relative price discounts increases sales in a flash sale e-commerce environment.

Herding and scarcity effects drive impulse buying behavior. Impulse purchases are made unintended, unreflective, and immediate, which means that not all consequences of buying are taken into account [41]. Liberal return policies support impulse ordering, as they detach the final buying decision from the ordering decision. At the moment of ordering, product valuation is increased by an emotional surplus [27]. After receiving the product, consumers assess the utilitarian and hedonic performance of the product, which might not meet expectations.

Furthermore, costs can outweigh the benefits after an impulse purchase episode, leading to negative emotions such as regret and dissatisfaction, although the product has no objectively identifiable shortages [42]. A way out of these negative emotions is returning the product [43]. This aligns with Gardner and Rook [44], who describe impulse buyers as less happy with their purchases. Furthermore, impulsive purchases are usually less aligned with real tastes and needs [2] due to the ordering pressure. Therefore, we conclude in agreement with [23, 27–29, 45] that impulse buying behavior triggered by scarcity messages could increase the probability of returning a product:

H3. Displaying product scarcity increases returns in a flash sale e-commerce environment.

Highlighting relative price discounts leads to different, opposite effects. On the one hand, price discounts reduce customer expectations, as a lower quality will be considered acceptable [46]. On the other hand, high discounts promote impulse purchases with a higher uncertainty regarding quality and fit. Additionally, as justified previously, impulse purchases are more likely to cause negative emotions or regret. We believe that the effect of impulse buying predominates, and therefore, we conclude:

H4. Displaying relative price discounts increases returns in a flash sale e-commerce environment.

3. Methodology

3.1. Data source and structure

For our study, we collaborated with a large flash sale e-tailer located in the European Union. The e-tailer provided comprehensive campaign-level real-world data on time-limited discounted sale campaigns. This approach surpasses the most frequent approach in returns management, consumer self-reports: Many empirical problems such as social desirability or recall bias do not apply, as actual purchases are observed. Sample selection bias cannot be completely ruled out, but the collaborating retailer assured us that no particular data set was picked, so we assume this selection is random.

The retailers' assortment mainly focuses on fashion products such as apparel, shoes, and accessories. Sale campaigns are only accessible by a closed community. This means no external customers can be attracted, e.g., via price search engines. Sales are brand-specific and are scheduled in advance. The retailer offers free returns within 14 days with no questions asked.

Table 1. Dataset description

Variable (Mean / SD)	Description
RetPrice (69.08 / 58.77)	Recommended retail price (RRP)
DiscPrice (27.50 / 22.85)	Discounted product price (DP)
AbsDisc (39.11 / 36.27)	Difference between RRP and DP
RelDisc (58.78 % / 7.53 %)	Discount in percent
RelDiscDisp (92.76 % / 25.92 %)	Dummy variable for products with the relative discount displayed (above 50 %)
RelDisc*RelDiscDisp (55.63 % / 16.58 %)	Interaction: value of the displayed discount
ItemsSold (4.76 / 6.29)	Number of sold items per product
ItemsRet (1.03 / 1.60)	Number of returned items per product
ReturnRate (21.66 % / 26.71 %)	Return rate (weighted by ItemsSold)
ProdRev (84.28 / 114.23)	Revenue of a product (before returns)
InitialStock (45.41 / 51.90)	Initial stock level of the product
StockDisp (.18 / .38)	Dummy variable for products with at least 1 item sold disclosing low stock
StockDispProp (.13/.31)	Proportion of sold items per product disclosing low stock
Female (.60/.49) Male (.31/.46)	Dummy variables for female- and male-targeted products (reference: children and others)
CloseFit (.32/.47)	Dummy variable: close-fitted product

The dataset used for this study (see Table 1) consists of sales level data of 20 flash sale campaigns in the product categories apparel/shoes/accessories during the year 2019. To reduce noise, we filtered the data to apparel products only, which was the overwhelming majority of products sold. The campaigns were exclusively directed to the German market, the largest national e-commerce market in the European Union. If a product was sold out during a campaign, reordering and restocking were impossible for the retailer. The 20 campaigns contain 5,826 unique products sold at least once with an initial stock of at least five items. Variants (i.e., different sizes or colors) are each counted as independent products. The average number of items sold for a product equals 4.76, which results in 27,725 items sold with a total order value of 490,992 €. In sum, 6,005 items were later returned (21.66 %).

3.2. Operationalization

Methodologically, this paper is based on parametric statistical methods (t-test and multivariate regression). The dependent outcome variables for sales are the number of ordered items (Model 1a) or the revenue of a product before returns (i.e., number of ordered items * discounted price, Model 1b). For returns, we use the relative return rate of a product (Model 2), which is calculated by the number of returned items in proportion to the number of sold items.

Our study aimed to examine two independent factors in detail: displaying information about low stock and the relative price discount. Both informational interventions are designed to be subtle enough to act as digital nudges according to the nudging categories identified by Meske and Potthoff [13]. Scarcity messages ("Only x items left") inform the customer about the products' availability without clearly urging customers to order quickly, as there was no message such as "Order now before it gets unavailable". These messages were displayed from the point when the available stock dropped to 5 items. The message contained the actual number of items left in stock, which means that the retailer did not fake low stock. This variable was operationalized by a dummy, indicating whether at least one product was sold when the stock was displayed (i.e., remaining stock < 5). For closer examination, we modeled the proportion of items sold with the stock message displayed to the customer. If a product with an initial stock of 10 items and 7 items sold had 2 items sold with a low stock message displayed, *StockDispProp* is calculated as 2/7 = 0.29, whereas a product with an initial stock of 5 and 4 items sold leads to *StockDispProp*=1.

Displaying the relative discount frames the customer's decision to price aspects and acts as a simplification for customers since they do not need to determine the relative discount themselves. It served as additional promotion as it was only displayed when above 50 %. The recommended retail price and discounted price were always visible to the customer. We operationalized the conditional display as an interaction term of the relative discount and the dummy variable whether the information was shown or not. This term is either 0 or ranges between 0.5 and 1.

First, we controlled for the product price, as the empirical evidence that a higher price induces more returns is consistent [1, 3, 18, 47]. Second, we controlled for the effects of the product target group (female/male/children and others). Women are supposed to be the customer group with the highest return rate [3], so we expect women's products to be returned more often as well. Next, we controlled for close-fitted apparel such as lingerie, pajamas, or leggings, as fitting issues are the most important reason for returning an apparel purchase [48]. There is still a higher degree of fit uncertainty in close-fitting products because the customer cannot try those on before delivery. Finally, we controlled for a product's initial stock and the absolute discount, which customers can easily estimate since both recommended retail and discounted prices are displayed.

4. Data analysis results

4.1. Preliminary analysis

To test our hypotheses, we first used t-tests to compare products for which at least one item was sold with a low stock message and those for which the message was never displayed (Table 2).

Table 2. Two-sample t-test analysis

	No low stock display	Low stock display	T (df)	p
ItemsSold	4.68 (6.39)	5.11 (5.77)	2.14 (1649)	.03
ProdRev	69.93 (96.18)	150.08 (158.77)	15.69 (1214)	<.01
ReturnRate	19.28 % (25.24)	31.66 % (30.15)	27.76 (7212)	<.01
	No discount display	**Discount display**	**T (df)**	**p**
ItemsSold	5.09 (5.95)	4.73 (6.31)	-1.11 (5824)	.27
ProdRev	74.02 (79.50)	85.08 (116.47)	2.64 (572.71)	<.01
ReturnRate	16.50 % (20.23)	22.09 % (27.14)	11.95 (2836)	<.01

For the relative return rate, we weighted the data by the number of items sold. Regarding H1, we observe a significant increase in sales in terms of items sold and product revenue. This suggests a substantial influence on the product price and leads to biased results, so in the next step, the price needs to be controlled for. Regarding

H3, the return rate is significantly larger for products bought with a low stock message displayed.

Comparing the groups that show the relative discount or not, an increase in sales is inconclusive (H2). Contrary effects of the number of sold items and product revenue emphasize the need for an in-depth analysis. However, the return rate is significantly higher for products with a displayed discount (H4).

4.2. Regression analysis of sales

First, we estimated two linear regression models (1a and 1b) with the items sold and product revenue as dependent variables. The independent variables included two nudges (proportion of sold items when low stock is displayed and relative discount display) and all previously introduced controls (Table 3). In general, both models are significant. Concerning the quality of the model, the employed independent variables explained 7.5 % and 25 % of the response variable variance.

The findings support H1: *StockDispProp* significantly increases sales, as indicated by Models 1a and 1b. The promotional effect is moderate in comparison to the control variables (Beta = .04). If a product shows the remaining stock for the whole campaign, it increases the number of items sold by 0.75, and the product revenue increases by 13.22€ compared to a product that does not show the scarcity message. Against this, H2 needs to be rejected. Although Model 1a shows a minimal and significant positive effect of the displayed relative price discount, this variable is insignificant in Model 1b and changes direction. Managerially, it can be seen that the display of discounts has a much smaller influence on the order probability than the amount of the discount.

Regarding the control variables, products for women or men are sold less frequently than those for children or an undefined target group. Nevertheless, the differences between the target groups are low and not consistent in Models 1a and 1b. Close-fitted products result in higher revenue, but this variable is not significant for the number of items ordered. The most considerable relative influence is the price and the amount of the discount. The initial stock level correlates with sales because low stock levels limit the maximum possible sales of a product.

4.3. Regression analysis of returns

For testing H3 and H4, we estimated a linear model with a product's relative return rate as the dependent variable (Model 2 in Table 3). In general, the model is significant and explains 20 % of the return rate's variance. Table 3 presents the results in detail.

Since *StockDispProp* is significant with a positive algebraic sign, H3 is supported: Products with a scarcity message displayed throughout the campaign increase the return rate by 3.79 percentage points. This is in line with H1, which suggests an increase in impulse purchases, leading to a higher level of order regret or more unfulfilled expectations. For this reason, the positive sales effect of this nudge must be carefully weighed against the negative impact due to the associated higher returns. In addition, customers may order a product of different sizes to ensure that one item fits well, especially for highly attractive products with low remaining stock [3], resulting in an increased likelihood of returns.

The absolute discount, which was not directly displayed to the customer, and the dummy for close-fitted fashion is not significant at the alpha=.05 level. Additionally, the display of a relative discount above 50 % is only significant at the alpha=.1 level. When the relative discount is displayed, the return rate is significantly increased by .02 percentage points, which is a very limited effect. This is not surprising, as no increase in impulse buying behavior can be

Table 3. Results of the linear regression models

	Model 1a (ItemsSold)			**Model 1b** (ProdRev)			**Model 2** (ReturnRate, weighted by items sold)		
Variable	**B (SE)**	**Beta**	**p**	**B (SE)**	**Beta**	**p**	**B (SE)**	**Beta**	**p**
StockDispProp	.75 (.28)	.04	.01	13.22 (4.52)	.04	<.01	3.79 (.62)	.04	<.01
RelDisc*RelDiscDisp	.02 (.01)	.05	<.01	-.13 (.09)	-.02	.15	.02 (.01)	.01	.08
Controls									
DiscPrice	-.07 (.01)	-.25	<.01	1.62 (.12)	.32	<.01	.48 (.02)	.38	<.01
AbsDisc	.02 (.00)	.11	<.01	.76 (.07)	.24	<.01	.01 (.01)	.01	.67
InitialStock	.02 (.00)	.18	<.01	.27 (.03)	.12	<.01	-.01 (.00)	-.03	<.01
Female	-.65 (.32)	-.05	.04	-13.20 (5.21)	-.06	.01	7.25 (.58)	.13	<.01
Male	-.26 (.34)	-.02	.45	-18.71 (5.56)	-.08	<.01	-1.72 (.62)	-.03	.01
CloseFit	-.03 (.19)	.00	.86	13.10 (3.07)	.05	<.01	-.30 (.32)	.01	.34
(Constant)	4.28 (.36)		<.01	13.09 (5.83)		.03	6.94 (.63)		<.01
F (df, p value)	59.90 (8, <.01)			242.19 (8, <.01)			865.05 (8, <.01)		
R^2	.075			.250			.200		

demonstrated by the discount display (see H2). Another explanation is that flash sale customers are used to high discounts, and this nudge does not change the valuation uncertainty. Moreover, it is worth noting that this type of nudge can prevent customer dissatisfaction, as Peinkofer et al. found that heavily discounted products are more likely to be accepted as sold out [49].

The most influential control variable is discounted price (B=.48; Beta=.38). This indicates that the likelihood of returns increases with the price level of an ordered item, replicating the results from empirical returns management literature [e.g., 1, 47]. Based on our data, we quantify that a 10€ higher price increases the relative article-based return rate by approximately 1 percentage point. Regarding the other control variables, products for women have a 7.25 percentage point higher return rate than products for children or others. In comparison, the return rate of products for men is 1.72 percentage points lower. With the slightly lower number of women's products ordered, discounts for men's products can eventually be calculated more tightly from a managerial point. These products are ordered more often and returned less frequently and thus entail less unwanted expenses. In contrast to the models for sales, the absolute amount of the discount is not a significant factor and does not exert a relevant influence on the return rate despite its significance.

5. Synthesizing the sales and returns perspective: A quantitative model

The preceding data analysis demonstrated that advertising artifacts such as the display of low available stock affect both sales and returns, that is, the marketing and logistics/operations perspective. However, do such measures pay off, or would e-tailers be better off without them? Mollenkopf et al. [50] emphasized that it is crucial for the success of an e-tailer not to consider only one view in isolation but to integrate both.

To this end, a comparative quantitative model is introduced that allows an objective assessment of whether such measures are beneficial. The analysis is based on the realized contribution margins and draws on the general conditions and relationships described in Asdecker [17]. Table 4 provides an overview of the parameters used.

The model compares two scenarios. In scenario 1, the status quo, the company tries to promote impulse purchases with the measures examined in this paper and accepts the known return rate. In scenario 2, it is assumed that the company forgoes these measures, which reduces the number of returns and orders.

Table 4. Model Parameter

Symbol	Description
TCM_{SQ}	Total contribution margin with electronic marketing measures (e.g., display of low stock) → status quo
TCM_{NO}	Total contribution margin without electronic marketing measures
ORD	Number of ordered items in the planning period in the status quo
ΔORD	Percentage change in ordered items (%) after omission of the marketing measures
RR	Average return rate (%) of an ordered item in the status quo
ΔRR	Percentage change in the average return rate (%) after omission of the marketing measures
P	Average selling price of the ordered items
C	Average wholesale price of the ordered items
RC	Average cost of a returned item
DC	Average distribution costs of the ordered items (e.g., shipping, picking, packing)

The omission of the advertising measures is beneficial if $TCM_{SQ} < TCM_{NO}$. The total contribution margin in the status quo (TCM_{SQ}) consists of the number of ordered items multiplied by the per item contribution margin, which in turn depends on the share of retained items (1-RR), the retail margin (P-C), the return rate (RR), the return costs (RC), and the distribution costs (DC):

$$TCM_{SQ} = ORD \cdot \left((1 - RR) \cdot (P - C) - RR \cdot RC - DC \right)$$

If the electronic marketing measures are omitted (TCM_{NO}), the percentage changes regarding the number of ordered items (ΔORD) and the return rate (ΔRR) need to be taken into account:

$$\begin{aligned} TCM_{NO} = ORD \cdot (1 + \Delta ORD) \cdot \Big(\big(1 - \big(RR \cdot (1 + \Delta RR)\big) \cdot (P - C)\big) \\ - RR \cdot (1 + \Delta RR) \cdot RC - DC \Big) \end{aligned}$$

By comparing the two scenarios and solving the inequation $TCM_{SQ} < TCM_{NO}$ for ΔORD, we can now determine the maximum acceptable reduction in demand if omitting the advertising measures reduces the return rate by ΔRR:

$$\Delta ORD > -\frac{RR \cdot \Delta RR \cdot (P - C + RC)}{(P - C) \cdot \big(1 - RR \cdot (1 + \Delta RR)\big) - DC - RC \cdot RR \cdot (1 + \Delta RR)}$$

For a specific product on sale, the average return rate is 30.77 %. According to the regression model, not displaying information about a low stock can reduce the return rate by 1.89 percentage points, corresponding to a relative decrease of ΔRR=-6.16 %. Furthermore, the flash sale e-tailer that provided the dataset indicated that the following parameter values appear realistic for their business model: P=27.50 €; C=13.75 € (equivalent to a 50 % commission); RC=5 €; DC=3 €.

For these values, it follows that ΔORD>-6.64 % (i.e., the omission of the displayed information is only justified if the number of orders decreases by a maximum of 6.64 %). The regression for the specific numerical example predicts a decrease in orders by 8.9 %, which indicates that the nudge should remain active. However, if return costs were close to 7.50 € (see Figure 1 for sensitivity with varying return costs), the decision would have to be reversed.

Figure 1. Sensitivity analysis

It shows that a decision for or against a measure always has to be made on a case-by-case basis, that it depends on the respective conditions, and that it should not be driven by a functional perspective (sales vs. returns). The model may serve as a basis for a decision support model that objectifies the underlying issue. It mainly fits flash sale e-tailers since no additional costs due to remarketing occur in their business model. Unsold stock is returned to the brand manufacturers. However, simple adjustments can be made to account for these costs as well.

6. Conclusion

Motivated by the hypothetical but typical situation of a flash sale customer, we addressed whether displaying quantity scarcity and price discounts affect sales and returns and how this impacts profitability. This paper delivers three findings:

- Displaying low stock messages in a flash sale e-commerce environment promotes sales and increases the rate of returns.
- Highlighting the relative price discount neither boosts sales nor does it imply relevant higher returns.
- The presented quantitative model can evaluate this trade-off.

Thus, what is the theoretical contribution of this paper? According to Whetten [51], contributions arise from four categories: (1) factors to explain a phenomenon (what?), (2) the relationship between those factors (how?), (3) logical justifications for altered views (why?), and (4) conditions that limit generalizability.

We contribute primarily to the factors for sales and returns and their relationship by confirming the positive effect of low stock messages (i.e., quantity scarcity) on sales (H1 accepted) in flash sale e-commerce [22, 23]. Unlike previous contributions, this is the first study to focus on fashion flash sales and the peculiarities of this specific product category. The same contribution type (what and how?) applies to the increase of the relative return rate (H3 accepted).

The results strengthen the recently published study by Calvo et al. [23] that investigates the effect at a flash sale e-tailer with a broad product assortment from toys to home appliances. They also assess the overall impact on profitability by referring to net sales as a proxy. Net sales are defined as the number of sold items minus returns: “[B]ecause the firm’s returns are […] slightly above 5 % […], and the cost of a return compares with the margin of a sale […], the average treatment effect is very large (+12.5 % in net sales) […]” [23]. They furthermore conclude that “[t]he positive effects on […] profitability amplify over wide assortments […].” However, as we show, it is necessary to integrate the financial perspective, namely, contribution margins and costs, to draw conclusions about profitability. To our understanding, net sales are a measure with limited suitability for assessing overall profitability. Instead of relying on net sales, we contribute a generalizable quantitative model assessing actual profitability based on cost and revenue parameters to better substantiate the decision-making. In our numerical example, the sales loss forecast by the regression outweighs the savings due to fewer returns. Nevertheless, these results may vary depending on the prerequisites of the dealer, the sales campaign, and the product. By this generalization, we contribute to the “why”. Although this research specifically relates to flash sales, the results may also apply to a broader context, including shopping situations that entail a purchase decision under pressure (e.g., Amazon Prime Day or regular “deals of the day”).

Furthermore, to the best of our knowledge, this study is the first to investigate the impact of relative discount disclosure on both sales and returns. The results show that the effect of this nudge (H2 and H4 rejected) remains negligible compared to the display of the stock level. This adds to the findings of Luo et al. [19], who investigated this effect only concerning sales.

Managerially, this research highlights that decision-makers must keep in mind both sides of the medal when designing nudges for e-commerce websites, that is, sales and returns. At first glance, integrating such nudges appears attractive as they are quick and easy to implement at virtually no cost. However, the devil is in the details. High return rates and costs can destroy the desired profitability of an instrument [52]. The introduced quantitative model can objectify such decisions. The conducted sensitivity analysis shows that it is always case-sensitive, which calls for machine-learning approaches that identify products for which the display or omission of such nudges is beneficial.

Our study is not free of limitations. It is based on data from a single flash-sale e-tailer with data from their German customer community, limiting generalizability. Furthermore, we cannot determine whether the display of the scarcity message exclusively causes the observed effects or if unobserved factors exaggerate these effects. Furthermore, the additional variance explained by the display of low stock or relative discounts remains modest. This hints at a repeated analysis with more detailed data, for instance, by revealing the timing of sales and integrating customer- and product-based attributes for the sales and returns model. The analysis also calls for a replication using data from different countries since German customers are characterized by unique high-returning behavior [53]. The observed return rates (< 25 %) are lower than those found in the literature for “classical” fashion e-commerce (up to 60 % [54]). Nevertheless, in combination with the synthesized quantitative model for assessing profitability, we are confident that our findings are helpful for practitioners from e-tailers and other scholars researching this topic.

7. References

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